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14. ABSTRACT
Human-system integration (HSI) is a complex process used to design and develop systems that integrate human capabilities and limitations in an effective and affordable manner. Effective HSI incorporates several domains including manpower, personnel, and training, human factors, environment, safety, occupational health, habitability, survivability, logistics, intelligence, mobility, and command and control. To achieve effective HSI, the relationships among these domains must be considered. Although this integrated approach is well documented, there are many instances where it is not followed. Human factors engineers typically focus on system design with little attention to the skills, abilities, and other characteristics needed by human operators. When problems of fielded systems occur, additional training of personnel is developed and conducted. Personnel selection is seldom considered during the HSI process. Complex systems such as aviation require careful selection of the individuals who will interact with the system. Personnel selection is a two-stage process involving *select-in* and *select-out* procedures. Select-in procedures determine which candidates have the aptitude to profit from training and represent the best investment. Select-out procedures focus on medical qualification and determine who should not enter training for medical reasons. The current paper discusses the role of personnel selection in the HSI process in the context of remotely-piloted aircraft systems.

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Personnel Selection Influences on Remotely-Piloted Aircraft Human-System Integration

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Introduction: Human-system integration (HSI) is a complex process used to design and develop systems that integrate human capabilities and limitations in an effective and affordable manner. Effective HSI incorporates several domains including manpower, personnel, and training, human factors, environment, safety, occupational health, habitability, survivability, logistics, intelligence, mobility, and command and control. To achieve effective HSI, the relationships among these domains must be considered. Although this integrated approach is well documented, there are many instances where it is not followed. Human factors engineers typically focus on system design with little attention to the skills, abilities, and other characteristics needed by human operators. When problems of fielded systems occur, additional training of personnel is developed and conducted. Personnel selection is seldom considered during the HSI process. Complex systems such as aviation require careful selection of the individuals who will interact with the system. Personnel selection is a two-stage process involving *select-in* and *select-out* procedures. Select-in procedures determine which candidates have the aptitude to profit from training and represent the best investment. Select-out procedures focus on medical qualification and determine who should not enter training for medical reasons. The current paper discusses the role of personnel selection in the HSI process in the context of remotely piloted aircraft systems.

Key Words: remotely piloted aircraft, human-system integration, personnel selection

Achieving high levels of effectiveness cannot be done for complex systems such as remotely piloted aircraft (RPA) solely through technological advances. Systems such as RPA consist of hardware, software, and personnel which must effectively work together to achieve organizational objectives. Human-systems integration (HSI) is a comprehensive management and technical approach to address the role of human operators in system development and acquisition (2, 23). HSI incorporates several domains including manpower, personnel, and training, human factors, environment, safety, occupational health, habitability, survivability, logistics, intelligence, mobility, and command and control (30). These domains are interdependent. They must be considered in terms of their interrelationships, and considered early in the system development and acquisition process to be effective. Booher (2) carefully delineates each of the domains noted above. Researchers and practitioners are cautioned against concluding that consideration of a plurality or even a majority of them is sufficient. Rather, it is necessary to consider each of them as well as their interactions to achieve effective human- system integration.

It is difficult and costly, if not impossible, to "fix" a poorly designed complex system once built and implemented. Complex systems, such as those found in aviation, require careful selection of the individuals who will interact with them. The current paper focuses on the role of personnel selection in HSI for remotely piloted aircraft (RPA) systems. We expand on a recent paper by Carretta and King (7) as we discuss the role of personnel measurement and selection for HSI, the development of US Air Force Undergraduate RPA Training (URT) selection standards, other important considerations in personnel selection, and expected changes in selection requirements as RPAs evolve.

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ROLE OF PERSONNEL MEASUREMENT AND SELECTION FOR HSI

Those responsible for human-system integration should be aware of the relations between selection, training, and human-system design and how they interact to affect overall system effectiveness. Poor personnel measurement and selection will result in higher training attrition and training costs, increased human-system integration costs, lower levels of job performance, and reduced safety. Poor selection may have long-term consequences for organizations such as the military where management and leadership are developed from within the organization.
Failure to consider factors related to leadership potential during the selection process will make it difficult for organizations to grow or remain operationally effective.

Poor training will require higher quality applicants and improved human-systems design to mitigate its effects. If these higher-quality applicants are not available, the consequences will be overall increased training costs due to higher attrition and/or the need to provide additional training to achieve the desired level of proficiency or possibly a reduction in the quality of some training graduates.

Poor human factors (i.e., clumsy automation, operator-vehicle interface design) will increase operator cognitive demands and workload, resulting in increased selection and training requirements. Effective selection (8) and training (22, 27) methods and human-automation interaction (21) can help reduce life cycle costs and contribute to improving organizational effectiveness.

THE DEVELOPMENT OF URT SELECTION STANDARDS

US Air Force RPA Pilot Selection Methods

In the US Air Force, early efforts to field RPA systems focused on technology development. The initial manning approach for RPA systems was to retrain manned aircraft pilots to operate RPAs. There were no RPA-specific selection requirements to evaluate the suitability of manned aircraft pilots for RPA systems. Personnel selection, training, and human-interface design were given little attention as it was assumed that experienced manned aircraft pilots could operate RPAs effectively following some platform-specific training. Although this approach was mostly effective, as demand for the capabilities provided by RPAs increased, it became too costly and unsustainable. In 2009, the Undergraduate RPA Training (URT) program was established to train personnel with no prior flying experience to operate RPAs. URT curricula were developed and selection requirements based on those for manned aircraft pilot training were established.

URT selection methods involve both *select-in*-and *select-out* procedures and are very similar to those for manned aircraft pilot training. Aptitude testing (select-in) and Medical Flight Screening (select-out) are two important factors. Aptitude testing includes the Air Force Officer Qualifying Test (AFOQT; 14), Test of Basic Aviation Skills (TBAS; 4), and Pilot Candidate Selection Method (PCSM; 5). Aptitude requirements for URT qualification are identical to those for manned aircraft pilot training. Medical Flight Screening (MFS) includes successful completion of a FAA Class III Medical Certificate and an USAF Flying Class IIU Medical Examination (29), review of medical records, psychological testing, and an interview. Results from the MFS psychological testing and interview are not used as part of a select-out process with strict minimum qualifying scores. Rather, a licensed psychologist uses clinical judgment to assess the psychological disposition of URT applicants to determine whether there is an aeromedically disqualifying condition in accordance with Air Force guidelines (29). Results of two recent USAF predictive validation studies for URT (6, 26) have demonstrated similar levels of validity for the AFOQT Pilot and PCSM composites to those observed for manned aircraft pilot training.

Results for studies examining the utility of personality for URT are less consistent (11, 26). Chappelle, McDonald, Heaton, Thompson, and Haynes (11) examined the predictive validity of the AFOQT Pilot composite, Revised NEO Personality Inventory (NEOPI-R; 12), and a neuropsychological battery, the MicroCog (24) versus URT completion. The best-weighted regression composite for predicting URT completion included the AFOQT Pilot composite, several NEO-PI-R scales, and the MicroCog Reaction Time subtest. Discriminant analyses showed that the personality scales of the NEO PI-R improved classification accuracy (identification of true positives and true negatives) beyond that provided by cognitive ability and prior flight time. Classification accuracy improved from 57.1% to 75.2% when personality scores were included, but the authors do not indicate which of the “Big Five” personality traits (the domains of Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness) were predictive. Moreover, the results for the personality scores should be viewed with some caution as they likely capitalized on chance given the large number of

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NEO- PI-R scales (particularly if the authors used each of the five domains' respective six facet scales) relative to the small sample size.

Rose, Barron, Carretta, Arnold, and Howse (26) examined the extent to which scores from the Self-Description Inventory (SDI+; 18), a Big Five measure of personality, could improve prediction of URT completion and training grades beyond the AFOQT Pilot and PCSM composites. Regression analyses showed no incremental validity for personality scores when used in combination with the AFOQT Pilot or PCSM composite scores for predicting URT completion. However, the Openness score demonstrated small, but statistically significant incremental validity for predicting the initial RPA qualification-training grade.

RPA System Job/Task Analyses

Despite the predictive validity of current RPA pilot training selection methods, several studies have been conducted to determine whether there are any unique job-related skills, abilities, and other characteristics (SAOCs) not adequately measured by current selection methods (for a summary, see 9, 33). In the Williams, Carretta, Kirkendall, Barron, Stewart, and Rose study (33), Air Force, Army, and Navy subject matter experts in personnel measurement, selection, and testing identified and assigned importance ratings to 115 SAOCS that appeared in one or more military RPA job/task analyses. Where available, psychometric data were examined for existing Department of Defense (DoD) and US Military Service proprietary personnel selection and classification tests to 1) determine the extent to which the tests measure critical RPA SAOCs and to 2) identify measurement gaps. Seventy-eight of the 115 SAOCs received an average rating of 3 (moderately important) or higher on a 5-point scale. Of these, 57 of 78 (73%) were judged to be measured by one or more existing military proprietary tests. It is interesting to note that many of the most important SAOCs involved personality (e.g., conscientiousness, stress management, dependability, vigilance, adaptability/flexibility, integrity, responsibility, self- discipline). Table 1 provides examples of the highest-rated cognitive, personality/temperament, and other characteristics. See Williams et al. (33) for the complete list of SAOCs.

Williams et al. (33) made several recommendations regarding RPA operator test battery content. As previously noted, most of the critical SAOCs were judged to be measured by existing proprietary DoD or US Military Service tests. They recommended that a program beestablished to increase the reliability and reduce the fakeability of military personality tests such as the Naval Aviation Trait Facet Inventory (NATFI, http://www.med.navy.mil/sites/nmotc/nami/Pages/ASTBOverview.aspx), Naval Computer-Adaptive Personality Scales (NCAPS; 15), Self-Description Inventory (SDI+; 18), and the Tailored Adaptive Personality Assessment System (TAPAS; 28). They also recommended development of new tests to fill measurement gaps (e.g., oral comprehension, vigilance) and to improve experimental measures involving task prioritization/multi-tasking and work preferences (person-environment fit).

Table 1. Examples of SAOCS Rated Most important for RPA Pilots

Cognitive	Personality/ Temperament	Other
Task Prioritization	Conscientiousness	Time Sharing
Oral Comprehension	Stress Management/ Tolerance	Control Precision
Spatial Orientation	Dependability	Occupational Interests/ Work Preferences, P-E Fit
Oral Expression	Vigilance (ability & personality)	
Attention to Detail	Adaptability/Flexibility	
Critical Thinking	Responsibility	
	Self-Discipline	

OTHER IMPORTANT CONSIDERATIONS IN PERSONNEL SELECTION

The Criterion

Many researchers spend enormous amounts of effort to develop measures of critical SAOCs based on the results of job/task analyses. They then search for available, convenient, or easy-to- collect job performance criteria with little thought about the theoretical meaning or psychometric properties of the criteria. The same care used to develop personnel selection methods and predictors of job performance should go into the development of job performance criteria.

Failure to consider the psychometric properties of the criterion (e.g., construct validity, dimensionality, discriminability, reliability) leads to incorrect decisions about the effectiveness of selection methods and their relation to job performance. Problems also are caused by inattention to contamination, deficiency, and relevance of the criterion.

As with measures used for personnel selection, job performance criteria vary in the constructs they measure, content, and specificity. To the extent possible, the constructs assessed by the job performance criteria should have a theoretical relationship to those measured by the selection measures. As we have discussed, RPA job/task analyses have identified several critical personality traits needed for success. However, predictive validation studies have shown relatively low validities for personality compared to cognitive and other measures. One reason for this finding may be the job performance criteria used in these studies do not capture constructs for which personality is important (these traits include effort, leadership, and indicators of maladaptive or counterproductive behavior). McHenry, Hough, Toquam, Hanson, and Ashworth (19) provided an example that demonstrates the importance of criterion specificity. McHenry et al. administered a large battery of measures including ability and personality/temperament to a sample of US Army trainees. Multiple criteria were used to reflect different aspects of job performance. Cognitive tests were the best predictors of criteria reflecting technical job proficiency, while measures of personality/temperament were the best predictors of criteria reflecting effort and leadership.

Special Population Norms

The assessment of human characteristics is based on comparing an individual to a representative sample of the population. Certain segments of the population vary significantly from the general population. For example, groups may differ on level of academic achievement, physical fitness, job experience, specialized knowledge/training, or other factors related to occupational performance. Moreover, differences in personality across occupational groups such as engineers, pilots, and sales personnel may occur. Military aircrew personnel are a highly selected and distinguished occupational group. Competition for pilot training assignments is great, with the result that those selected differ significantly from the general adult population on cognitive, personality, and other characteristics considered during the selection process.

Carretta, Teachout, Ree, Barto, King, and Michaels (10) reported cognitive and personality norms for large samples of US Air Force pilot trainees. They observed that the mean full-scale IQ score for this group (M = 120, SD = 6.63) was about 1.33 standard deviations above the normative adult population mean (M = 100, SD = 15). A pilot with a mean full-scale IQ of 105 would be slightly above the normative adult population mean, but over two standard deviations below the mean for US Air Force pilot trainees using the pilot normative values (M = 120, SD = 6.63).

Significant differences also have been observed for personality scores of US Air Force pilot trainees compared to adult population norms. The personality portion of the USAF Neuropsychiatrically Enhanced Flight Screening (17) program, the forerunner of MFS, was developed to compile special population norms. The battery has been composed of the 1) Armstrong Laboratory Aviation Personality Survey (ALAPS; 25) and 2) NEO Personality Inventory-Revised (NEO-PI-R; 13). The ALAPS measures personality, psychopathology, and crew interaction, while the NEO-PI-R measures the previously delineated "Big Five" domains and their facets of normal personality. Figure 1 illustrates the number of standard deviations USAF pilot normative means are above or below those for the adult general population. Similar specialized norms are not presented for the ALAPS because it was normed on a USAF student pilot sample.

To date, over 26,000 USAF student pilots have been administered some combination of these psychological tests. King, Barto, Ree, and Teachout (16) presented a compendium of specialized USAF personality testing norms that can be used with military pilots and, cautiously, with applicants for civil airlines. This report includes profile sheets tailored specifically with these norms. A perusal of these norms demonstrates that USAF pilots differ from the general population on commercially published test norms. For example, this population has a mean *Agreeableness* T-score of 44.12 and a mean *Extraversion* T-score of 57.41, while the general population, by definition, has mean T- scores of 50 for both. This information is helpful when assessing individual pilots, as it places them in the proper context relative to their peers. The Armstrong Laboratory Aviation Personality Survey may not be useful to those in the civilian sectors of aviation due to Federal law (the Americans with Disabilities Act) concerns, as it can be used to diagnose psychopathology in addition to measuring desirable personality traits. The problem would be administering it as part of a select-in procedure and violating Federal law by asking select-out type questions before extending a conditional employment offer. Further, it may be problematic as a selection tool due to the availability of the test manual (25) in the open literature, encouraging coaching schemes, which could

contribute to response inflation.

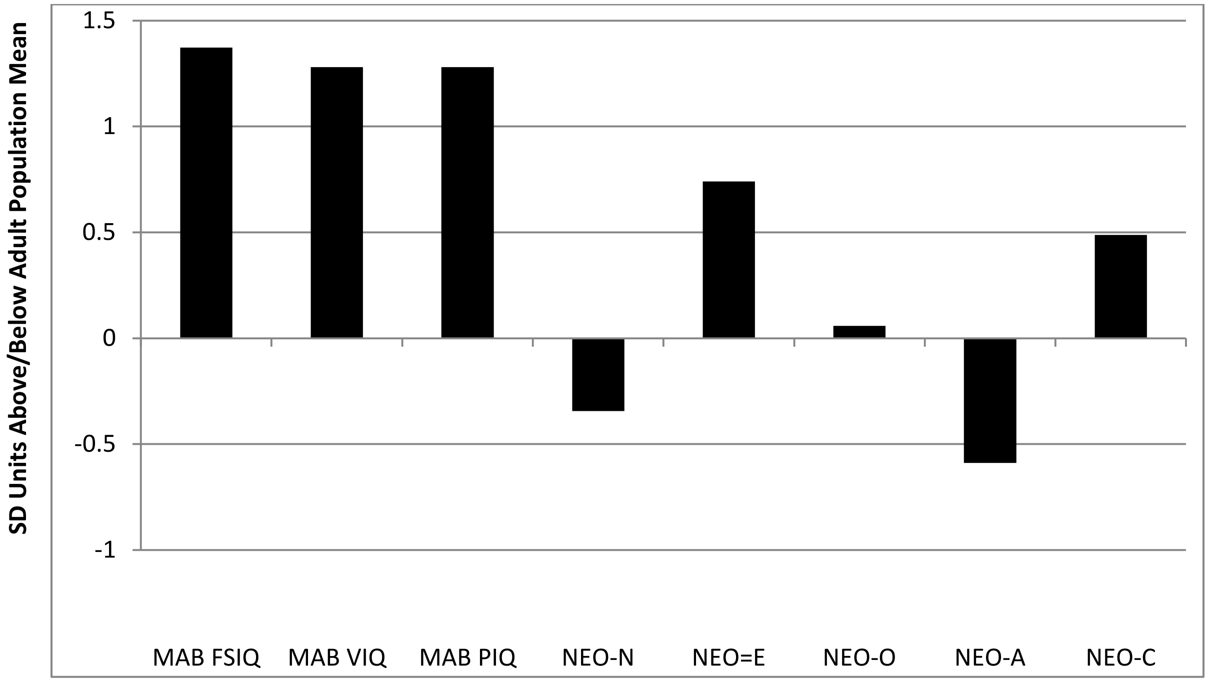

Figure 1. US Air Force pilot trainee norms versus the adult general population. The scores are the Multidimensional Aptitude Battery (MAB) Full-Scale IQ (FSIQ), Verbal IQ (VIQ), and Performance IQ (PIQ) and the NEO-PI-R Neuroticism (HEO-N), Extraversion (NEO-E), Openness (NEO-O), Agreeableness (NEO-A), and Conscientiousness (NEO-C) scores. Differences are expressed in standard deviation (SD) units above or below the population normative mean.

Response Inflation

Response inflation or "faking good" is a consequence of positive impression management. It is common in employment applications where personnel measurement includes assessment of personality/temperament and/or interests. Applicants typically put their "best foot forward" by responding in such a way as to match their idea of how an ideal candidate would respond to indicate high suitability for a desired job. Self-report measures of Big Five personality constructs are particularly susceptible to response inflation (1). Impression management by job applicants may not necessarily be a bad thing. Employers would be wise to avoid candidates who do not attempt to create a positive impression during the selection process. Ones and Viswesvaran (20) contend that response inflation does not invalidate applicants' testing. They also noted that the ability to engage in such behavior "may be regarded as an aspect of social competence" (p. 256), certainly an asset in most jobs. Even technical jobs, such as those in aviation, have a social element that is important for organizational success. Therefore, applicants naturally wanting to make a positive impression are likely to exaggerate their positive qualities and minimize those they consider negative when confronted with personality testing. Williams and King (32) compared results for air traffic controllers on a validity scale and found that less response inflation was observed for *research participants* who completed psychological testing under no job jeopardy (i.e., the results would not impact their job prospects), than for *job applicants*. Williams and King suggested that the job applicants were putting their best foot forward.

We recommend that practitioners review Butcher, Morfitt, Rouse, and Holden (3) for one strategy to handle the problem of impression management in the form of response inflation when selecting among job applicants. Butcher et al. specifically coach applicants not to inflate their responses. It also should be noted that not all personality tests (e.g. NEO PI-R; 13) contain impression management scales. Measuring the extent of response inflation can help practitioners determine if test results should be viewed with caution and if it is advisable to correct for the inflated scores. In any case, scores on validity scales, when available, can give practitioners a sense of how the applicant approached the assessment process. These scales are especially useful when specialized population norms are available, particularly if collected under conditions of job jeopardy.

That is not to say that efforts should not be made to reduce score inflation. To this end, the US Army has developed a computer-adaptive Big Five personality test, the Tailored Adaptive Personality Assessment System (TAPAS; 28), which is propriety to the US Army. The TAPAS attempts to control for faking through a forced choice format where pairs of statements have been equated for social desirability.

POTENTIAL IMPACT OF NEW TECHNOLOGY ON RPA OPERATOR SAOC REQUIREMENTS

RPA pilot SAOC requirements may be affected by mission objectives (e.g., manned- unmanned teaming, multi-RPA control), technology (e.g., automated take-off and landing, improved human-system interface design), and working conditions (e.g., work stressors such as shifts, number of hours, workload). It is likely that as technology advances, unmanned systems will become more autonomous, automated, and intelligent and more integrated with other manned and unmanned assets in a net-centric environment. Some tasks currently requiring manual control (take offs, landings, mission planning, sensor control) may be handled by automated systems, only requiring consent/approval by human operators. Decision aids (e.g., automatic target recognition, route planning, and timeline management) will enable the operator to assume more of a supervisory role in an integrated human-system team (31). Technological developments may enable supervisory control of multiple RPAs or possibly swarms by a single operator. Under such conditions, mental and temporal workload will be high. SAOC requirements will focus on higher-order cognitive functioning. As aircraft autonomy increases, the need for manual flight control and psychomotor ability will decrease in importance. It is important that those responsible for human-system integration periodically examine the impact of changes in mission objectives and work environment and new technology on manpower, selection, and training requirements.

Discussion

Those responsible for human-system integration should carefully consider all of the characteristics of human actors when developing or modifying systems. First, a job/task analysis must be done, including an analysis of cognitive, personality and other psychological characteristics needed for job success. Comparisons to the general population can be misleading. The use of specialized norms, when available and not prohibited by Section 106 of the Civil Rights Act of 1991, is highly recommended when assessing applicants as well as trained assets. People, unlike machines, are prone to put their best foot forward (engage in response inflation) in an effort to influence decisions affecting job opportunities. Efforts should be made to determine the extent to which score inflation occurs on personality/temperament tests as due to impression management by applicants. Measures (e.g., validity scales) should be included to determine the magnitude of score inflation due to impression management or to mitigate the amount of inflation through testing procedures (e.g., special instructions, using response options that control for social desirability). Practitioners would be wise to consider disregarding test results if validity scales are highly elevated. Finally, those responsible for human-system integration should bear in mind the effects of changes in mission objectives and work environments and advances in technology on manpower, personnel, and training requirements, as well as systems safety and human factors engineering. Above all, HSI requires an appreciation that the integrated system is much greater than the sum of its parts.

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